**Human Capital Efficiency and Equity Funds’ Performance during the COVID-19 pandemic.**

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**Abstract**

The paper investigates the impact of human capital efficiency (HCE) on equity funds’ performance during three stages of the COVID-19 pandemic. We collected data for 799 open-ended equity funds across five EU countries and ranked them in five categories of HCE and compare their risk-adjusted performance across these categories. The results suggest that during the COVID-19 outbreak, the equity funds that were ranked higher in HCE outperformed their counterparts. We suggest that fund managers should invest in human capital to improve funds’ coping ability and resilience during periods of extreme stress.

**Keywords:** *COVID-19, mutual funds, human capital efficiency, risk-adjusted performance.*

1. **Introduction**

In a rational setting, the funds with better-skilled managers should outperform their counterparts. There is a plethora of studies that focus on mutual funds performance and possible determinants of persistence. Andreu et al. (2018) attributed the market timing ability of mutual funds’ managers to the fund's size. Muñoz et al. (2014) documented the role of the clientele effect towards funds’ performance and suggested that funds’ management is influenced by profit-seeking and value-driven investors. Andreu et al., (2019) focused on risk-seeking of mutual funds and highlighted that managers’ demographics contribute towards risk profile and consequently impact the financial performance. Fang et al., (2017) believed that during recessionary periods, fund managers' skills are effected by herding behavior. Wang and Ko (2017) highlighted the importance of managers’ retention for persistent performance. Berkowitz and Kotowitz (2002) suggested that sustainable returns of mutual funds emanate from the quality of funds’ management, and investors are willing to pay higher fees to engage better quality fund managers. Many studies have deliberated on the positive linkages between managers’ skills and mutual fund performance (e.g., Berk & van Binsbergen, 2015; Yi et al., 2018; Cai et al., 2018; Muñoz, 2019). However, there is limited evidence on the impact of Human Capital Efficiency (HCE) on equity funds’ performance, and it is not clear whether this impact varies in different market conditions.

COVID-19 pandemic and its severe economic and social consequences provide unique settings to examine the effect of investment in human capital and its efficiency on the mutual funds’ performance. In this paper, we explore whether mutual funds with higher human capital efficiency demonstrate higher resilience to the COVID-19 crisis shock or not. The diverse impacts of the COVID-19 pandemic on financial markets and institutions have been analyzed in the recent literature from several sets of perspectives. Zhang et al., (2020) report a substantial increase in volatility in global markets due to the outbreak of the COVID-19. Corbet et al., (2020) explore the impact of corporate identity associations with ‘corona’ on the stock performance before and during the pandemic. Goodell & Huynh, (2020) assess the US industry-level market reactions to COVID-19 pandemic and COVID-related news announcements. Yarovaya et al., (2020) analyze the response of equity, bond, precious metals, and cryptocurrency markets to the COVID-19 shock, and results demonstrate heterogeneous patterns of reaction and recovery across different asset classes and within each class of assets. Goodell & Goutte, (2020) employed a wavelet coherence approach to investigate the Bitcoin reaction to the COVID-19 pandemic. The results indicate that during the peak of the pandemic, from 5th April to 29th April 2020, the levels of COVID-19 caused a rise in Bitcoin prices. A similar approach used by Sharif et al., (2020) in the analysis of the impact of the COVID-19, EPU, geopolitical index and oil price on the US stock markets in the first three months of the pandemic, from 21st January to 30th March 2020. Results show that oil shock hit the US stock markets stronger than the spread of the COVID-19 virus itself.

The economic effects originated by the COVID-19 pandemic has been explored across stock markets, commodities, and cryptocurrencies (Akhtaruzzaman et al., 2020; Corbet et al., 2020). The comprehensive overview of the COVID-19 contagion and unique characteristics of this new crisis is provided by Yarovaya, et al., (2020), while Goodell, (2020) further highlights the direction for future COVID-19 research. Owing to the active investment strategies, mutual funds usually act as panic healers and fund managers are expected to produce consistent positive alphas (Huang et al., 2019). Rizvi et al., (2020) reported varying mutual funds’ performance during the COVID-19 outbreak in EU. They also pointed out the drift in investment styles of fund managers as a response to the evolving situation. While new evidence on the economic effects of the COVID-19 rapidly become available, to our best knowledge, this paper is the first attempt to analyze the impact of investment in human capital on the coping mechanism of the mutual funds and their resilience to the COVID-19 crisis. The investment in human capital is very strategic (Hitt et al., 2001) and contributes to value creation (Lopez-Cabrales et al., 2006). The relevance of human resources increases manifold for services (Nieves & Quintana, 2018), and mutual funds represent an essential cluster of financial services that have significant dependence on human capital. Therefore, it is crucial to assess if mutual funds’ performance varies with human capital efficiency.

Thus, in this paper, we analyze the linkages between human capital efficiency and the mutual fund performance in five European economies that have been severely affected by the COVID-19 pandemic. This includes Spain, Italy, France, Germany, and Belgium, which account for 14.8% of the global cases and 28.4% of the mortality count (see Table 1 for COVID-19 statistics in these countries). Most of the early studies on the COVID-19 are focused on the US economy and impact on the US market (e.g., Sharif et al., 2020; Goodell & Huynh, 2020). In this paper, we consider the impact of investing in human capital on a sample of EU funds and assess their resilience towards the pandemic, providing novel and original contribution to the COVID-19 literature.

[Table 1 here]

The results show that funds with higher human capital efficiency depicted better risk-adjusted performance and Jensen’s alpha compared to their counterparts during the outbreak. This remains consistent across different stages of the COVID-19 crisis in five countries analyzed. We report that even when the pandemic reached its peak in the EU and the majority of funds demonstrated negative returns, the funds that are in the top 20% of human capital efficiency demonstrated positive (and higher) risk-adjusted returns. The findings remained robust for various performance measures as well as for abnormal returns assessment during pre-COVID and outbreak periods.

The remainder of the paper is organized as follows. Section 2 discusses the data and methodology. Section 3 presents empirical results, while Section 4 concludes.

**2. Data and Methodology**

This paper utilizes data for 799 open-ended equity funds across five countries, Spain, Italy, France, Germany, and Belgium, from the 1st of January to the 2nd of June 2020. The focus of this paper is to evaluate the impact of human capital efficiency on the performance of equity funds during the COVID-19 pandemics. Pulic (2000), Pulic and Kolakovic(2003) suggest that Human Capital Efficiency (HCE) is a function of value-added (VA) and human capital (HC) that can be expressed as:

 , (1)

where *HC* is an investment in human capital. The *VA* for a fund is estimated as a product of CAPM based fund’s alpha and asset under management (α x AUM).

 We estimate HCE for each fund as of 4Q19. The necessary information related to compensation and AUM is available from financial disclosures of each fund, and we only include funds that publicly disseminates these details. The compensation consists of payroll, commissions, bonuses, allowances, training expenditures, etc. that signify various spending on human resources in a given fund. Our final sample consists of 799 equity funds across five countries. To calculate the CAPM based alpha, we use daily net asset value (NAV) going back to January 2019 (pre COVID-19 period). The individual fund alpha, along with AUM, is used to estimate VA in equation 1. The value-added and investment in human capital will get us HCE. Once HCE for each fund is estimated, we classify them in five groups (20% each) from high to low HCE. The comparative performance is assessed across these groups during the COVID-19 outbreak. We expect that funds with higher HCE should outperform their counterparts with lower HCE. Table 2 presents the country-wise distribution of these funds across five rank groups.

[Insert Table 2 about here]

 We analyze the impact of the COVID-19 crisis on our ranked funds’ performance in several subperiods. We begin our assessment from January 1st, 2020, which is the date when COVID-19 was formally reported to WHO. Hence, our full period spans from January 1st to June 2nd, 2020. After that, we consider subperiods to analyze the performance during different stages of the COVID-19 pandemic. Stage A is specified from January 1st to February 20th, 2020, that marks a very moderate spread of the virus in the EU, i.e., an early stage of the crisis. Stage B is from February 21st to May 7th that represents the peak of the pandemics, and stage C is from May 8th to June 2nd when the curve begins to flatten. In Table 3, we present the timeline of these stages with some critical news corresponding to the evolution of the COVID-19 crisis.

[Insert Table 3 about here]

There are two methodological approaches that we employ in this study for evaluating the impact of HCE on the funds’ performance. The first one comprises the conventional risk-adjusted measures, while the second one is similar to an event study. These two approaches are explained below.

**2.1 Risk-Adjusted Performance**

To estimate and compare the risk-adjusted performance, we employ multiple measures. These include adjusted Sharpe (Sharpe, 1966), Treynor (Treynor & Mazuy, 1966), Sortino (Sortino & Price, 1994), and Information ratios. The adjusted Sharpe ratio is based on Sharpe (1966) and modified to by Pezier and White (2006) to account for non-normality of returns. Few modifications have been proposed for information ratio; however, Goodwin (1998) noted that the ratio in its simplest form is most useful for funds’ comparison. We supplement these ratios by calculating Jenson’s alpha (Jensen, 1968) using an asset pricing framework of Fama and French (1992) and augmented by Carhart (1997). The fixed effect panel representation of this will be:

, (2)

 where RX is (n x t) vector of funds’ NAV based returns in group *i* of HCE, Rf represents the risk-free rate, Rm – Rf is the market risk premium, *SMB* represents size premium, *HML* and *MoM* respectively reflect value and momentum factors. The Rf, as well as risk premia, are of the form (1 x t). Jensen’s alpha is represented by *α,* while *β*, *s*, *h,* and *w* are risk loadings. We use Euro 5 years’ government benchmark bond yield as the risk-free rate, European SMB, HML, and MoM factors are extracted from the data library of Kenneth R French[[2]](#footnote-2). For information ratio, we use S&P Europe 350[[3]](#footnote-3) as the benchmark.

2.2 Event Study Methodology

 Given the relevance of HCE, we expect that there should be a performance differential in pre Covid-19 and the outbreak periods. To evaluate this, we use a CAPM based event study methodology similar to that of Goddard et al., (2012) and Mirza et al., (2020). The mean and variance functional form of GARCH (1,1) will be as follows

 with  ……(3)

 …… (4)

*Rit* is the intraday fund return, *Rmt* corresponds to the returns on S&P Europe 350, *Rft* is the risk-free rate. We define *Dit* as the dummy variable with t = 1; if t falls during the COVID-19 outbreak (entire period as well as for each stage), *hit* is the fund’s conditional variance, and *eit* is random error. We represent estimated parameters as *αi*, *βi*, *ϕi*, *ci*, *ai*, *bi,* and *δi* (errors in variables). The cumulative abnormal returns (CARs) are estimated through coefficient *τi*. For this analysis, we include pre COVID-19 data from January 1st, 2019, while for COVID-19, the sample period and stages are the same as specified earlier.

**3. Results and Discussion**

 The descriptive statistics on HCE before the outbreak is presented in Table 4. In the full sample, the average values range from 0.86 (low) to 6.29 (high), representing a significant difference between the extreme categories. There are some interesting observations across the countries. In the low HCE category, Spanish equity funds have minimum efficiency (0.68). Among the high HCE classification, equity funds in Belgium are at the bottom. The funds based in Germany and France represent the best efficiency across all categories of HCE from low to high.

[Insert Table 4 about here]

The results of different risk-adjusted measures are presented in Table 5. The funds with higher HCE outperform their counterparts with lower HCE for the entire period. The funds that are included in the two lowest ranks of HCE have negative risk-adjusted returns. This has been consistent when the risk is defined as total risk (Sharpe), systematic risk (Treynor), downside risk (Sortino), or tracking error (Information ratio). Our Sharpe ratio for lowest HCE funds is -0.075 (Treynor -0.04, Sortino 0.005, IR -0.0105), while for the top HCE category, it is 0.033 (Treynor 0.017, Sortino, IR 0.002). These results are mostly significant at 1% and 5% level of significance. An interesting observation is the performance of funds across the HCE ranks. As we move from lower to higher HCE, the performance of funds improve significantly. This remains robust across all metrics and indicates the relevance of HCE towards the performance of equity funds.

Table 5 also presents the results for the three stages of the COVID-19 crisis. During phase 1 of the pandemic, all funds demonstrated positive performance, which is plausible because, at that time, none of the countries in our sample were significantly impacted. The contagion was mostly contained within China and some countries in the Asia Pacific. In terms of HCE, the funds in the high category remained dominant during this period, while for the funds with low HCE, risk-adjusted returns were lower, albeit positive.

 [Insert table 5 about here]

Stage 2 of our analysis presents the results for the most devastating period of COVID-19 in the EU. This was when Europe became the new epicenter of the disease, and financial systems across member states came under stress. We can observe that funds in three out of five HCE categories plunged into the negative zone. These low to medium HCE categories represent 60% of our total sample. The two classifications that have funds with high HCE continued to resist, and for these, we observe a Sharpe ratio of 0.023 and 0.0125. These results demonstrate the better coping ability of fund with higher HCE.

During stage 3, in the final subperiod analyzed, the curve flattened with regression in the growth of new and hospitalized cases. This enabled the states to revive the economic activity resulting in moderate improvement in the financial market. We observe this impact with modest amelioration in funds’ risk-adjusted returns. The influence of HCE remained consistent, and funds that are ranked higher in terms of HCE continued to perform better on all estimates. The Sharpe and Treynor ratio for low HCE funds was -0.0255 and -0.0160, respectively, that increased to 0.0006 and 0.0003 for medium HCE funds. Finally, for high HCE funds, the estimated Sharpe and Treynor ratios are 0.026 and 0.0134. These results are clear evidence of the fact that funds earn excess returns based on human capital efficiency, and higher HCE translates into higher risk-adjusted returns.

 We present results on Jensen’s alpha with four factors specification in Table 6. For the entire period, we report negative alphas for low HCE funds. The excess returns are positive for funds with mid to high HCE. We observe a maximum alpha of 0.0396 in the most human capital-efficient funds, signifying that superior funds’ performance is associated with human capital efficiency. The stage-wise results are similar to our findings on risk-adjusted performance with higher HCE funds dominating across the three periods. The low HCE funds showed positive alpha in stage 1 but became negative in later stages. For high HCE funds, the alpha consistently remained positive (and max) across the three periods.

[Insert table 6 about here]

The results for GARCH (1,1) and ARCH LM are presented in table 7. The ARCH LM statistics indicate the incidence of ARCH effects for the estimation period and validates the choice of GARCH (1,1) (Hansen & Lunde, 2005). The CARs for the pre-COVID and entire COVID period as well as stage-wise assessment, support the relevance of HCE. During the pre-COVID period, the funds in the top two HCE categories show positive abnormal returns while all other funds have negative CARs. This trend continues during the outbreak with positive CARs for higher HCE funds. The most interesting observation here is that funds in the top HCE category demonstrate higher CARs during the pandemic compared to the pre-COVID abnormal returns. This suggests a vital role of HCE for funds performance amidst economic turmoils. During each of the three stages, the high ranked HCE funds report superior abnormal returns compared to their counterparts with lower HCE. For stage 1, there are positive CARs for all funds, while as the health crisis deepens in stages 2 and 3, only the top two HCE categories of funds could sustain positive CARs. These findings suggest that human capital efficiency is central in shaping up a fund’s performance and helps in enduring resilience in turbulent times.

[Insert Table 7 about here]

**4. Conclusion**

The performance of mutual funds is dependent on the investment strategies employed by the portfolio managers. These managers represent the human capital of a fund, and investment in this resource contributes towards human capital efficiency. Consequently, this efficiency should translate into a performance that should vary according to the level of human capital efficiency. The COVID-19 is an unfortunate but unique opportunity to evaluate the impact of human capital efficiency (HCE) on funds’ performance during a period of extreme stress. We analyze this by sorting equity funds based on their HCE and ranking them in five categories from high to low. The comparative performance is assessed across these categories. Our results suggest that during the COVID-19 outbreak, the equity funds that were ranked higher in human capital efficiency outperformed their counterparts. The analysis for different stages of the outbreak revealed some interesting findings. As the contagion peaks in the EU, most funds showed negative returns and Jensen’s alpha. However, even during this stage, the funds with higher HCE continued to demonstrate resilience with significant positive risk-adjusted returns as well as Jensen’s alpha. Our analysis of abnormal returns confirms the importance of HCE as funds in higher HCE category demonstrated superior abnormal returns for pre COVID-19 period as well as during the outbreak. We conclude that mutual funds should concentrate on investing in human capital as resulting efficiency leads to robust performance during periods marked with uncertainties and turmoil.

**References**

Akhtaruzzaman, M., Boubaker, S., & Sensoy, A. (2020). Financial contagion during COVID–19 crisis. *Finance Research Letters*, 101604. https://doi.org/10.1016/j.frl.2020.101604

Andreu, L., Matallín-Sáez, J. C., & Sarto, J. L. (2018). Mutual fund performance attribution and market timing using portfolio holdings. *International Review of Economics and Finance*, *57*, 353–370. https://doi.org/10.1016/j.iref.2018.02.003

Andreu, L., Sarto, J. L., & Serrano, M. (2019). Risk shifting consequences depending on manager characteristics. *International Review of Economics and Finance*, *62*, 131–152. https://doi.org/10.1016/j.iref.2019.03.009

Berk, J. B., & van Binsbergen, J. H. (2015). Measuring skill in the mutual fund industry. *Journal of Financial Economics*. https://doi.org/10.1016/j.jfineco.2015.05.002

Berkowitz, M. K., & Kotowitz, Y. (2002). Managerial quality and the structure of management expenses in the US mutual fund industry. *International Review of Economics and Finance*, *11*(3), 315–330. https://doi.org/10.1016/S1059-0560(02)00099-0

Cai, B., Cheng, T., & Yan, C. (2018). Time-varying skills (versus luck) in U.S. active mutual funds and hedge funds. *Journal of Empirical Finance*, *49*, 81–106. https://doi.org/10.1016/j.jempfin.2018.09.001

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x

Corbet, S., Larkin, C., & Lucey, B. (2020). The contagion effects of the COVID-19 pandemic: Evidence from Gold and Cryptocurrencies. *Finance Research Letters*, 101554. https://doi.org/10.1016/j.frl.2020.101554

Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance*. https://doi.org/10.2307/2329112

Fang, H., Shen, C. H., & Lee, Y. H. (2017). The dynamic and asymmetric herding behavior of US equity fund managers in the stock market. *International Review of Economics and Finance*, *49*, 353–369. https://doi.org/10.1016/j.iref.2016.12.012

Goddard, J., Molyneux, P., & Zhou, T. (2012). Bank mergers and acquisitions in emerging markets: evidence from Asia and Latin America. *The European Journal of Finance*, *18*(5), 419–438. https://doi.org/10.1080/1351847X.2011.601668

Goodell, J. W. (2020). COVID-19 and finance: Agendas for future research. *Finance Research Letters*, *35*, 101512. https://doi.org/10.1016/j.frl.2020.101512

Goodell, J. W., & Goutte, S. (2020). Co-Movement of COVID-19 and Bitcoin: Evidence from Wavelet Coherence Analysis. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3597144

Goodell, J. W., & Huynh, T. L. D. (2020). Did Congress trade ahead? Considering the reaction of US industries to COVID-19. *Finance Research Letters*, 101578. https://doi.org/10.1016/j.frl.2020.101578

Goodwin, T. H. (1998). The information ratio. *Financial Analysts Journal*. https://doi.org/10.2469/faj.v54.n4.2196

Hansen, P. R., & Lunde, A. (2005). A forecast comparison of volatility models: Does anything beat a GARCH(1,1)? *Journal of Applied Econometrics*, *20*(7), 873–889. https://doi.org/10.1002/jae.800

Hitt, M. A., Bierman, L., Shimizu, K., & Kochhar, R. (2001). Direct and moderating effects of human capital on strategy and performance in professional service firms: A resource-based perspective. In *Academy of Management Journal*. https://doi.org/10.2307/3069334

Huang, R., Pilbeam, K., & Pouliot, W. (2019). Do actively managed US mutual funds produce positive alpha? *Journal of Economic Behavior and Organization*. https://doi.org/10.1016/j.jebo.2019.03.006

Jensen, M. C. (1968). The Performance of Mutual Funds in the Period 1945-1964. *The Journal of Finance*. https://doi.org/10.2307/2325404

Lopez-Cabrales, A., Valle, R., & Herrero, I. (2006). The contribution of core employees to organizational capabilities and efficiency. *Human Resource Management*. https://doi.org/10.1002/hrm.20094

Mirza, N., Naqvi, B., Rahat, B., & Rizvi, S. K. A. (2020). Price Reaction, Volatility Timing and Funds’ Performance during Covid-19. *Finance Research Letters*, 101657. https://doi.org/10.1016/j.frl.2020.101657

Muñoz, F. (2019). The 'smart money effect’ among socially responsible mutual fund investors. *International Review of Economics and Finance*, *62*, 160–179. https://doi.org/10.1016/j.iref.2019.03.010

Muñoz, F., Vargas, M., & Vicente, R. (2014). Fund flow bias in market timing skill. Evidence of the clientele effect. *International Review of Economics and Finance*, *33*, 257–269. https://doi.org/10.1016/j.iref.2014.05.006

Nieves, J., & Quintana, A. (2018). Human resource practices and innovation in the hotel industry: The mediating role of human capital. *Tourism and Hospitality Research*. https://doi.org/10.1177/1467358415624137

Pezier, J., & White, A. (2006). The Relative Merits of Investable Hedge Fund Indices and of Funds of Hedge Funds in Optimal Passive Portfolios. *ICMA Centre Discussion Papers in Finance*, 1–32.

Pulic, A. (2000). VAIC - an accounting tool for IC management. *International Journal of Technology Management*. https://doi.org/10.1504/ijtm.2000.002891

Pulic, A., & Kolakovic, M. (2003). Value creation efficiency in the new economy. *Global Business and Economics Review*. https://doi.org/10.1504/gber.2003.006201

Rizvi, S. K. A., Mirza, N., Naqvi, B., & Rahat, B. (2020). Covid-19 and asset management in EU: a preliminary assessment of performance and investment styles. *Journal of Asset Management*, 1–11. https://doi.org/10.1057/s41260-020-00172-3

Sharif, A., Aloui, C., & Yarovaya, L. (2020). COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. *International Review of Financial Analysis*, *70*, 101496. https://doi.org/10.1016/j.irfa.2020.101496

Sharpe, W. F. (1966). Mutual Fund Performance. *The Journal of Business*. https://doi.org/10.1086/294846

Sortino, F. A., & Price, L. N. (1994). Performance Measurement in a Downside Risk Framework. *The Journal of Investing*. https://doi.org/10.3905/joi.3.3.59

Treynor, J. L., & Mazuy, K. K. (1966). *Can mutual funds outguess the market? Harvard Business Review 44*.

Wang, Y., & Ko, K. (2017). Implications of fund manager turnover in China. *International Review of Economics and Finance*, *51*, 99–106. https://doi.org/10.1016/j.iref.2017.05.004

Yarovaya, L., Brzeszczynski, J., Goodell, J. W., Lucey, B. M., & Lau, C. K. (2020). Rethinking Financial Contagion: Information Transmission Mechanism During the COVID-19 Pandemic. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3602973

Yarovaya, L., Matkovskyy, R., & Jalan, A. (2020). The Effects of a “Black Swan” Event (COVID-19) on Herding Behavior in Cryptocurrency Markets: Evidence from Cryptocurrency USD, EUR, JPY and KRW Markets. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3586511

Yi, L., Liu, Z., He, L., Qin, Z., & Gan, S. (2018). Do Chinese mutual funds time the market? *Pacific Basin Finance Journal*, *47*, 1–19. https://doi.org/10.1016/j.pacfin.2017.11.002

Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Research Letters*, 101528. https://doi.org/10.1016/j.frl.2020.101528

**Table 1: COVID-19 Statistics for Selected EU Countries**

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| --- |
|  |
| **Country** | **Total Cases** | **Total Deaths** | **Death Rate\*** |
| *World* | *6408816* | *378317* | *5,90%* |
| Spain | 286718 | 27127 | 9,46% |
| Italy | 233197 | 33475 | 14,35% |
| France | 189220 | 28833 | 15,24% |
| Germany | 183898 | 8636 | 4,70% |
| Belgium | 58615 | 9505 | 16,22% |
| Source: https://www.worldometers.info/  |  |
| The data is as on June 2nd, 2020 |  |  |
| \*Death Rate is calculated as Total Deaths/Total Cases |  |

**Table 2: Country wise Sample Distribution (Based on HCE)**

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|  |
|   | **Low** | **2** | **3** | **4** | **High** | **Total** |
| Spain | 21 | 26 | 20 | 25 | 26 | **118** |
| Italy | 24 | 22 | 19 | 33 | 27 | **125** |
| France | 42 | 42 | 48 | 42 | 45 | **219** |
| Germany | 52 | 50 | 54 | 49 | 47 | **252** |
| Belgium | 21 | 19 | 18 | 10 | 17 | **85** |
| **Total** | **160** | **159** | **159** | **159** | **162** | **799** |

**Table 3: Timeline of Evolution of COVID-19**

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| --- |
|  |
| Stage A | Dec 31 - Jan 01 | Chinese Authorities alert WHO about pneumonia type cases |
| Jan 11 | First death reported |
| Jan 21 | Human to Human transmission of virus confirmed by WHO |
| Jan 25 | Primary cases in Europe - France confirms three infections |
| Jan 27 | Germany confirms its first case |
| Jan 30 | WHO declares the outbreak a public health emergency |
| Feb 9 | The death toll surpass that of SARS epidemic in 2002-03 |
| Feb 11 | The official name COVID-19 is assigned to the virus |
| Feb 15 | France reports its first death |
| Feb 20 | The virus impacts 26 countries across the globe |
| Stage B | Feb 21 | Cases of COVID-19 continue to increase in Italy |
| Feb 28 | WHO raises the global risk of spread of COVID-19 from “high” to “very high.” |
| March 7 | The number of COVID-19 cases surpasses 100,000. |
| March 9 | COVID-19 is declared as global pandemic |
| March 13 | Europe is the new epicenter of disease with more cases and deaths than the rest of the world combined |
| March 17 | France imposes strict lockdown to combat COVID-19 |
| March 24 | Cases of COVID-19 crosses 400000 |
| April 3 | Asian Development Bank estimates economic impact of COVID-19 to be between $2 - $4 trillions |
| April 6 | The death toll in Europe crosses 50000 |
| April 22  | WHO observes the outbreak in Europe to be stabilizing |
| May 1 | European Investment Bank and WHO announces partnership for the COVID-19 response |
| May 4 | Italy begin to lift lockdown |
| May 7th | The UN increases its global response plan to $7 Billion |
| Stage C | May 8 | EU agrees on emergency financial support to euro area countries |
| May 11 | France lifts lockdown to ease certain restrictions |
| May 15 | EU discuss priorities for recovery |
| May 19 | EU adopts scheme to support workers |
| May 21 | Total number of cases crosses 5 million globally |
| May 25 | Relief measures were adopted for aviation and railways in EU |
| June 2 | France enters second phase of post lockdown, |

**Table 4: Human Capital Efficiency Year End 2019**

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|  |
|   |   | **Low** | **2** | **3** | **4** | **High** |
| **Overall** | Mean | 0,8615 | 1,5044 | 2,7120 | 4,7970 | 6,2926 |
| *Std Dev* | *0,0329* | *0,2093* | *0,3530* | *0,4229* | *0,6746* |
| **Spain** | Mean | 0,6853 | 1,2423 | 2,5708 | 4,9810 | 6,1528 |
| *Std Dev* | *0,0317* | *0,2334* | *0,2591* | *0,4984* | *0,5202* |
| **Italy** | Mean | 0,8484 | 1,1827 | 2,5064 | 3,5690 | 6,4507 |
| *Std Dev* | *0,0175* | *0,2417* | *0,4081* | *0,4145* | *0,5126* |
| **France** | Mean | 0,9331 | 1,8127 | 2,8932 | 5,3750 | 6,4206 |
| *Std Dev* | *0,0341* | *0,2096* | *0,4449* | *0,3718* | *0,5527* |
| **Germany** | Mean | 0,9720 | 1,9738 | 2,9713 | 5,5191 | 6,3811 |
| *Std Dev* | *0,0296* | *0,1400* | *0,3870* | *0,5171* | *0,8085* |
| **Belgium** | Mean | 0,8689 | 1,3109 | 2,6189 | 4,5420 | 6,0577 |
| *Std Dev* | *0,0456* | *0,2067* | *0,2043* | *0,2616* | *0,8849* |

**Table 5: Risk Adjusted Performance Measures**

|  |
| --- |
|  |
| **Full Period** |
|   | **Sharpe Ratio** | **Treynor Ratio** | **Sortino Ratio** | **Information Ratio** |
| **Low** | -0,0751 | \*\*\* | -0,0406 | \*\*\* | -0,0202 | \*\*\* | -0,0105 | \*\*\* |
| **2** | -0,0320 | \*\* | -0,0165 | \* | -0,0076 |  | -0,0037 | \* |
| **3** | 0,0019 | \* | 0,0009 | \* | 0,0004 | \*\* | 0,0002 | \*\* |
| **4** | 0,0284 | \*\*\* | 0,0103 | \*\* | 0,0052 | \*\* | 0,0023 | \*\* |
| **High** | 0,0332 | \*\* | 0,0175 | \*\* | 0,0054 | \*\* | 0,0022 | \*\* |
| **Stage 1** |
|   | **Sharpe Ratio** | **Treynor Ratio** | **Sortino Ratio** | **Information Ratio** |
| **Low** | 0,0065 | \*\*\* | 0,0046 | \* | 0,0015 | \*\* | 0,0032 |  |
| **2** | 0,0089 | \* | 0,0060 | \*\* | 0,0018 | \*\* | 0,0062 | \*\* |
| **3** | 0,0098 | \*\* | 0,0063 | \* | 0,0017 |  | 0,0093 | \*\*\* |
| **4** | 0,0192 | \*\* | 0,0117 | \*\* | 0,0029 | \* | 0,0154 | \* |
| **High** | 0,0269 | \*\*\* | 0,0197 | \*\*\* | 0,0036 | \*\*\* | 0,0263 | \* |
| **Stage 2** |
|   | **Sharpe Ratio** | **Treynor Ratio** | **Sortino Ratio** | **Information Ratio** |
| **Low** | -0,0689 | \*\*\* | -0,0109 | \*\* | -0,0349 | \*\* | -0,0090 | \*\* |
| **2** | -0,0479 | \*\* | -0,0072 | \*\* | -0,0214 |  | -0,0056 | \*\* |
| **3** | -0,0255 | \*\* | -0,0037 | \*\* | -0,0100 |  | -0,0027 | \* |
| **4** | 0,0125 | \* | 0,0017 | \*\* | 0,0043 | \*\* | 0,0012 | \*\* |
| **High** | 0,0230 | \*\*\* | 0,0200 | \*\* | 0,0070 | \*\*\* | 0,0133 | \*\*\* |
| **Stage 3** |
|   | **Sharpe Ratio** | **Treynor Ratio** | **Sortino Ratio** | **Information Ratio** |
| **Low** | -0,0255 | \*\* | -0,0160 | \*\*\* | -0,0042 | \*\*\* | -0,0092 | \* |
| **2** | -0,0103 | \* | -0,0062 | \*\* | -0,0015 | \*\* | -0,0034 | \*\* |
| **3** | 0,0006 |  | 0,0003 | \* | 0,0007 |  | 0,0002 | \* |
| **4** | 0,0174 | \*\* | 0,0094 | \*\*\* | 0,0020 |  | 0,0046 | \* |
| **High** | 0,0260 | \*\* | 0,0134 | \*\*\* | 0,0026 | \*\*\* | 0,0062 | \*\*\* |

Note: \*\*\* represents significance at 1%, \*\* at 5% and \* at 10%.

**Table 6: Jensen's Alpha based on Four Factor Model**

|  |
| --- |
|  |
| **Full Period** |
|  | **Low** | **2** | **3** | **4** | **High** |
| α | -0,0269 | \*\*\* | -0,0148 | \*\* | 0,0136 | \*\* | 0,0229 | \*\* | 0,0396 | \*\*\* |
| β | 0,7238 | \*\* | 0,6695 | \* | 0,3641 | \*\* | 0,1308 | \* | 0,2131 | \*\* |
| s | 0,5942 | \*\* | 0,6297 |  | 0,4802 | \* | 0,4418 | \*\* | 0,8938 | \*\* |
| h | 0,1071 | \* | 0,2255 | \*\* | 0,4510 |  | 0,6682 |  | 0,2383 | \*\* |
| w | 0,6105 | \*\* | 0,5813 |  | 0,2243 |  | 0,6049 | \* | 0,5456 | \*\* |
| Adj R2 | 0,6260 |  | 0,3090 |  | 0,3993 |  | 0,4586 |  | 0,5437 |  |
| Stage 1 |
|  | **Low** | **2** | **3** | **4** | **High** |
| α | 0,0054 | \*\* | 0,0061 | \*\* | 0,0092 | \* | 0,0108 | \*\* | 0,0187 | \*\*\* |
| β | 0,1190 |  | 0,3387 |  | 0,2482 | \*\* | 0,2172 | \* | 0,0554 | \*\* |
| s | 0,0249 | \*\* | 0,1057 | \*\* | -0,0857 |  | 0,1055 | \* | 0,0883 | \*\* |
| h | 0,1415 | \* | -0,2978 |  | 0,5958 | \*\* | 0,8827 | \* | 0,3148 | \* |
| w | 0,5780 | \*\* | 0,5504 | \*\* | 0,2124 | \*\* | 0,5727 | \*\* | 0,5166 | \* |
| Adj R2 | 0,3841 |  | 0,3995 |  | 0,4645 |  | 0,4602 |  | 0,5811 |  |
| Stage 2 |
|  | **Low** | **2** | **3** | **4** | **High** |
| Α | -0,0092 | \*\* | -0,0106 | \*\* | -0,0205 | \*\* | 0,0020 | \*\* | 0,0063 | \*\*\* |
| Β | 0,1295 | \* | 0,3688 | \* | 0,2702 | \* | 0,2365 | \*\* | 0,0603 | \*\* |
| s | 0,0262 | \* | 0,1111 |  | -0,0901 |  | 0,1109 | \* | 0,0928 | \* |
| h | 0,1555 | \*\* | 0,3274 | \* | -0,6550 |  | -0,9705 | \*\* | 0,3461 | \* |
| w | -0,6380 |  | 0,6075 | \* | 0,2344 | \* | 0,6321 | \* | 0,5703 | \* |
| Adj R2 | 0,4803 |  | 0,3032 |  | 0,3725 |  | 0,3723 |  | 0,4713 |  |
| Stage 3 |
|  | **Low** | **2** | **3** | **4** | **High** |
| α | -0,0109 | \*\* | -0,0085 | \*\* | 0,0094 | \*\* | 0,0173 | \*\* | 0,0202 | \*\*\* |
| β | 0,1023 | \* | 0,2912 | \* | 0,2134 | \* | 0,1868 | \* | 0,0476 | \* |
| s | 0,0508 | \*\* | 0,2156 |  | -0,1748 |  | 0,2152 | \*\* | 0,1800 | \*\* |
| h | 0,1869 | \* | -0,3934 |  | -0,7869 |  | -1,1659 |  | 0,4158 |  |
| w | 0,8270 | \*\* | 0,6198 | \* | -0,8633 |  | 0,2688 | \* | 0,3426 | \* |
| Adj R2 | 0,4693 |  | 0,4938 |  | 0,3107 |  | 0,4058 |  | 0,5913 |  |
| \*\*\* represents significance at 1%, \*\* at 5% and \* at 10% |

|  |
| --- |
| **Table 7: Abnormal Returns of HCE Sorted Funds Prior to Covid-19 and during Outbreak** |
| **Fund Type** |  |  | **Average Cumulative Abnormal Returns using GARCH (1, 1) CAPM Specification** |
|  | **Pre Covid** |  | **Covid Outbreak**  |  | **Stage 1** |  | **Stage 2** |  | **Stage 3** |   |
| **Low** | -0,0201% | \*\*\* | -0,0403% | \*\*\* | 0,0014% | \*\*\* | -0,0237% | \*\*\* | -0,0176% | \*\*\* |
| **2** | -0,0135% | \*\*\* | -0,0322% | \*\* | 0,0136% | \*\*\* | -0,0193% | \*\*\* | -0,0135% | \*\* |
| **3** | -0,0110% | \*\* | -0,0104% | \*\* | 0,0175% | \*\* | -0,0139% | \*\* | -0,0114% | \*\* |
| **4** | 0,0205% | \*\* | 0,0215% | \*\*\* | 0,0192% | \*\* | 0,0128% | \*\* | 0,0160% | \*\* |
| **High** | 0,0410% | \*\*\* | 0,0506% | \*\*\* | 0,0281% | \*\*\* | 0,0188% | \*\*\* | 0,0203% | \*\*\* |
|  |  |  |  |  |  |  |  |  |  |  |
| **Results of ARCH LM Test**  |  |  |  |  |  |  |  |  |  |
| **Category** | **No of Funds** | **Estimate** | **Test Statistic** | **Prob.** |  |  |  |  |  |  |
| **Low** | 160 | F-statistic | 10.449\*\*\* | 0.0001 |  |  |  |  |  |  |
|  |  | Obs\*R-squared | 9.141\*\*\* | 0.0001 |  |  |  |  |  |  |
| **2** | 159 | F-statistic | 5.583\*\* | 0.0002 |  |  |  |  |  |  |
|  |  | Obs\*R-squared | 5.461\*\* | 0.0190 |  |  |  |  |  |  |
| **3** | 159 | F-statistic | 5.256\*\* | 0.0195 |  |  |  |  |  |  |
|  |  | Obs\*R-squared | 5.147\*\* | 0.0199 |  |  |  |  |  |  |
| **4** | 159 | F-statistic | 6.236\*\* | 0.0112 |  |  |  |  |  |  |
|  |  | Obs\*R-squared | 6.287\*\* | 0.0115 |  |  |  |  |  |  |
| **High** | 162 | F-statistic | 7.706\*\*\* | 0.0027 |  |  |  |  |  |  |
|   |   | Obs\*R-squared | 7.454\*\*\* | 0.0029 |  |  |  |  |  |  |
| \*\*\*represent significance at 1%, \*\* at 5% and \* at 10% |  |  |  |  |  |  |

1. \* Corresponding author [↑](#footnote-ref-1)
2. The data library is open source and accessible at <http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html>

The factors’ daily data is available till April 30th 2020. Using Kenneth French methodology, we compute these factors for the remaining period (May 1st to June 2nd). The data is translated into equivalent of Euros. [↑](#footnote-ref-2)
3. The S&P Europe 350 consists of 350 leading blue-chip companies drawn from 16 developed European markets. [↑](#footnote-ref-3)